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Department of Earth, Atmospheric, and Planetary Sciences

6-7-2020

# A framework for analyzing ground effects of atmospheric rivers

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May 12, 2020 !

**Abstract**

Atmospheric rivers (ARs) are meteorological phenomena caused by filamented concentrated water vapor transport in the lower troposphere. Their variability has been found to link to floods and droughts. As the environment changes in part as a result of anthropogenic climate change, understanding ARs has become more important in the hopes of predicting what their local effects on the surface environment might be seen in the future. The purpose of this research is to build a workflow from data ingestion to analysis to find if there is correlation between the occurrence of atmospheric rivers and soil moisture, using the year of 2010 as an example. Although this research has found no such link, it is far from conclusive. More years of data as well as other soil moisture datasets may be beneficial to understanding the link between atmospheric rivers, soil moisture, and the human consequences of climate change.

## 1. Introduction

Atmospheric rivers (ARs) are areas of concentrated water vapor transport located primarily within the lowest 2.5 km of the atmosphere which are named for their narrow body (<1000 km) compared to their length (>=2000 km) (Neiman et al., 2008). They play an important role in the global water cycle and are relevant for the link between weather and climate.

One clear example is the relationship between atmospheric rivers and droughts and floods. The appearance of atmospheric rivers may increase the occurrence of floods by 80% while their absence may increase the presence of droughts by as much as 90% (Paltan et al., 2017). One area of the United States where this is particularly relevant is California. California's largest storms are the main provider of its water supply and are fueled by the landfall of atmospheric rivers which means the presence of ARs in the state can be the difference between a successful water year and drought (Dettinger et al., 2011). The other area is the central United States. In their hydrometeorological analysis of flood events from 1980 to 2011, Lavers and Villarini (2013) found that ARs are a major flood agent over the central United States.

With the well-known impact of ARs on the presence of droughts and floods, it could be a logical progression to believe there is a relationship between the presence of ARs and soil moisture. This research seeks to create a workflow to reveal the relationship between atmospheric rivers and soil moisture across the contiguous United States using monthly mean soil moisture data and atmospheric river frequency data. Specifically, the ARs that penetrated into the US Midwest and the contiguous US soil moisture data from 2010 were analyzed.

## 2. Data

The first primary dataset used in this research is the atmospheric river index dataset. The AR detection measurement is the Integrated Water Vapor (IWV) value calculated using the following equation:

$$\mathrm{IWV} = -\frac{1}{g}\int_{\mathbf{P_b}}^{\mathrm{P_t}} \big(q(p)\big)dp$$

where q is the specific humidity (kg kg$^{-1}$), $P_b$ is 1000 hPa, $P_t$ is 200 hPa, and g is the acceleration due to gravity (Shields et al., 2018). This was retrieved from the ARTMIP (Atmospheric River Tracking Method Intercomparison Project) dataset. In the ARTMIP dataset, IWV was calculated by the University of California, San Diego (UCSD) Center for Western Weather and Water Extremes (CW3E) by using the NASA Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) at 0.5° latitude x0.625° longitude (approximately 50 km x 50 km) spatial resolution and 3-hourly instantaneous temporal resolution (Shields et al., 2018). The presence of atmospheric rivers that penetrated into the US Midwest was determined using the 85$^{th}$ percentile monthly climatological thresholds applied to IWV fields and was generated in the form of 0s (no atmospheric river) and 1s (confirmed atmospheric river) (Zhang et al., 2020). The dataset ranges from January 1$^{st}$, 2006 through December 31$^{st}$, 2015, however, this project only uses data from January 1$^{st}$, 2010 through December 31$^{st}$, 2010. 2920 .csv files were generated, with each file representing a 3-hour time interval for the year 2010 at each latitude and longitude and whether or not an atmospheric river was present. The files also include the IWV values, however, this research does not make use of this information.

The CPC Soil Moisture data provided by the NOAA/OAR/ESRL PSL, Boulder, Colorado, USA, from their Web site at https://psl.noaa.gov/ in netCDF4 format. The datasets are version 2 and contain monthly means from January 1948 through January 2020 as of February 16$^{th}$, 2020 at 0.5°x0.5° spatial resolution. Values were generated by a one-layer hydrological model, which calculated soil moisture based on the water balance in the soil. This was calculated using precipitation, evaporation, runoff, and groundwater loss (Huang et al., 1996). There is no missing data, although the ocean contains 0s. The model assumes an effective holding capacity of 76 cm of water, meaning the maximum soil moisture is 760 mm (Fan and Dool, 2004).

This CPC Soil Moisture dataset is optimal due to its similar spatial resolution to that of the AR dataset. And, although its temporal resolution is far coarser, this ultimately is not an issue for the analysis involved and there is still a great deal of information that can be extracted by comparing the two datasets. This research uses soil moisture data from January through December of 2010 to coincide with the extracted AR data.

## 3. Methods

The methods for this research revolved around creating a workflow for processing and analyzing the datasets. A visual representation of this process can be seen in Figure 1 and was divided into three scripts: an organization script, spatial analysis script, and a visualization script. The organization script loads in and filters the AR data into 12 large data frames (one for each month) with the frequency of AR hits by location. The spatial script converts the soil moisture netCDF into similar data frames to the AR data frames but with moisture values instead of count and clips these data frames to the extent of the contiguous United States. It also uses a nearest neighbor spatial join to account for the spatial offset in the data, shown in Figure 2, and match each month's AR frequency data to the corresponding month's mean soil moisture data. These two scripts are separate and utilize cluster computing on Purdue's Brown Community High-Performance Computing Cluster due to their computationally intensive nature. The packages necessary for them include dplyr, lubridate, ncdf4, sp, rgdal, nngeo, and raster. The final script is used to visualize and analyze the data and requires the packages raster, lattice, RColorBrewer, and latticeExtra. A preliminary view of the datasets created using this script can be seen in Figure 3.

## 4. Results

In order to obtain a better understanding of the monthly mean soil moisture data, the mean of all twelve months was calculated and the difference between each monthly soil moisture and the yearly mean was found. The soil moisture anomalies can be seen in Figure 4, where negative values represent areas drier than the yearly mean and positive values represent areas wetter than the yearly mean.

After matching up the two datasets using nearest neighbor spatial join, a direct comparison between the atmospheric river hits and the monthly mean soil moisture was made using the visualization script. Figure 5 shows each monthly atmospheric river hit plotted against each monthly soil moisture anomaly. A linear regression was calculated for each month and yielded the R-squared values as described in Table 1. The results showed low R-squared values overall with the highest values being for April at 0.2937810367 and October at 0.2707995396. The April linear regression showed a negative correlation between atmospheric river hits and soil moisture anomalies while October showed a positive correlation between the two. Most of the R-squared values, however, were extremely low and showed that the two variables have no conclusive linear correlation.

A second linear analysis was performed by offsetting the datasets. The AR hits dataset was compared against the monthly soil moisture anomaly dataset one month ahead in Figure 6. This was done with the speculation that it may take time to see the effects of atmospheric rivers on soil moisture. The results were similar to the previous analysis in that there was very little evidence of a linear relationship. Some of the higher R-squared values were April at 0.2509346189, May at 0.2382372887, and November at 0.3226564206 with negative, negative, and positive correlations respectively.

The final visual analysis involved generating a scatterplot matrix (SPLOM) shown in Figure 7. This includes 24 variables, 12 months of soil moisture anomalies and 12 months of AR hits with each variable plotted against the others. The purpose of this figure is to find any relationships not yet considered and any other possible offsets. It looks as though there are no visible offsets for the year, but there are still some patterns that will be further discussed.

## 5. Discussion and Conclusions

Although there is no evidence of linear relationships between the variables investigated, there is still a potential relationship between atmospheric rivers and soil moisture. A constraint of this research was the short timeframe of the year 2010. A larger dataset spanning more years could reveal relationships that are not seen here. It is possible there is an offset relationship between atmospheric rivers and soil moisture anomalies that is greater than a single month and could be as large as 6 months or even a year. Additionally, this research assumed that in the offset relationship, atmospheric river hits were the leading factor, meaning they preceded monthly mean soil moisture. It is possible that soil moisture may play a role in the formation of atmospheric river systems and, therefore, precede them in an offset analysis. Any future relationships looked at may not be linear like this research assumes, so other methods should be considered.

One of the more useful figures generated in this research is the SPLOM in Figure 7. Although there is little evidence of a relationship between soil moisture and AR hits, there is an interesting relationship within the soil moisture dataset itself. There is evidence that each mean soil moisture month has a relationship with the following month. The relationship fades as the months get further apart. This could be a useful pattern to note for future research.

For future research, a longer dataset should be looked at as well as more atmospheric rivers than just those that make landfall in the US Midwest. Also, there is a soil moisture dataset provided by the Soil Moisture Ocean Salinity (SMOS) satellite that is not model generated and has a similar spatial resolution to the datasets used in this research. There is also potential beyond the correlation between atmospheric rivers and soil moisture. When deciding to investigate soil moisture, there were many other datasets that were considered such as socioeconomic, flood plain, and groundwater data. All of these have the potential to show a relationship with the presence of atmospheric rivers, but the right dataset to match the required resolutions must be found.

## 6. Figures (

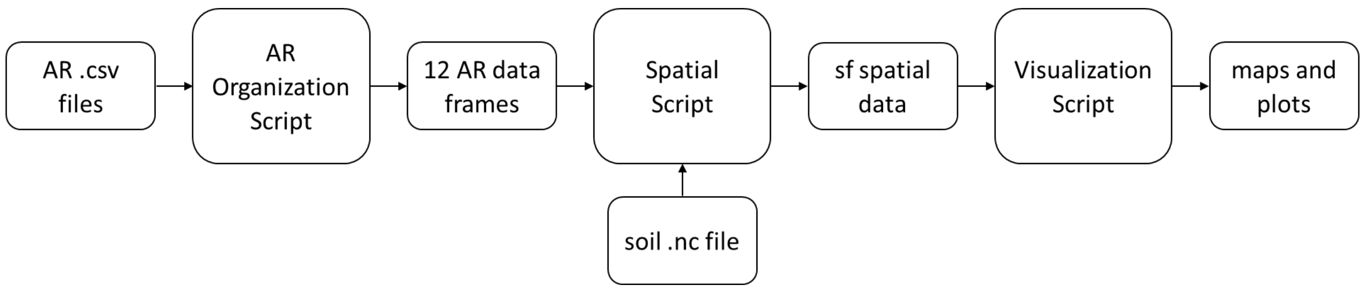



Figure 1: Representation of workflow. The larger boxes represent scripts while the smaller boxes represent inputs and outputs.

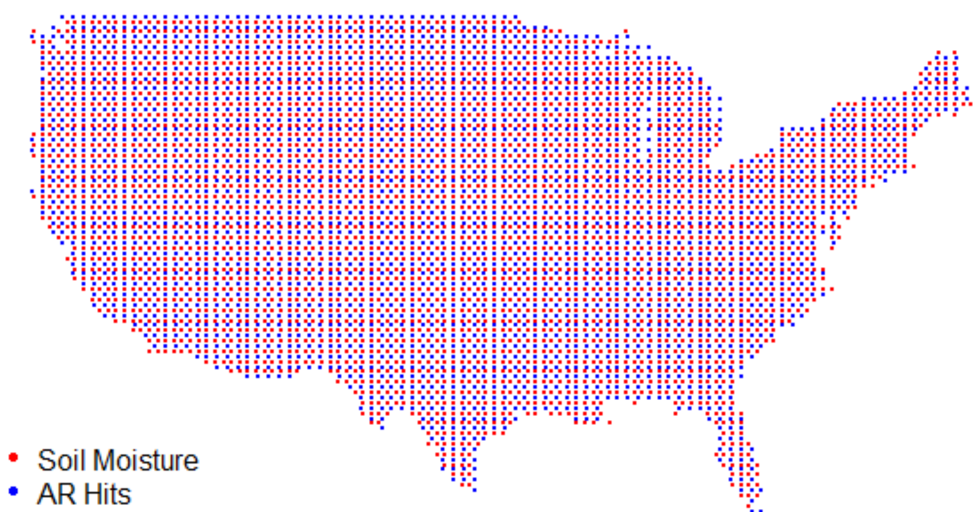
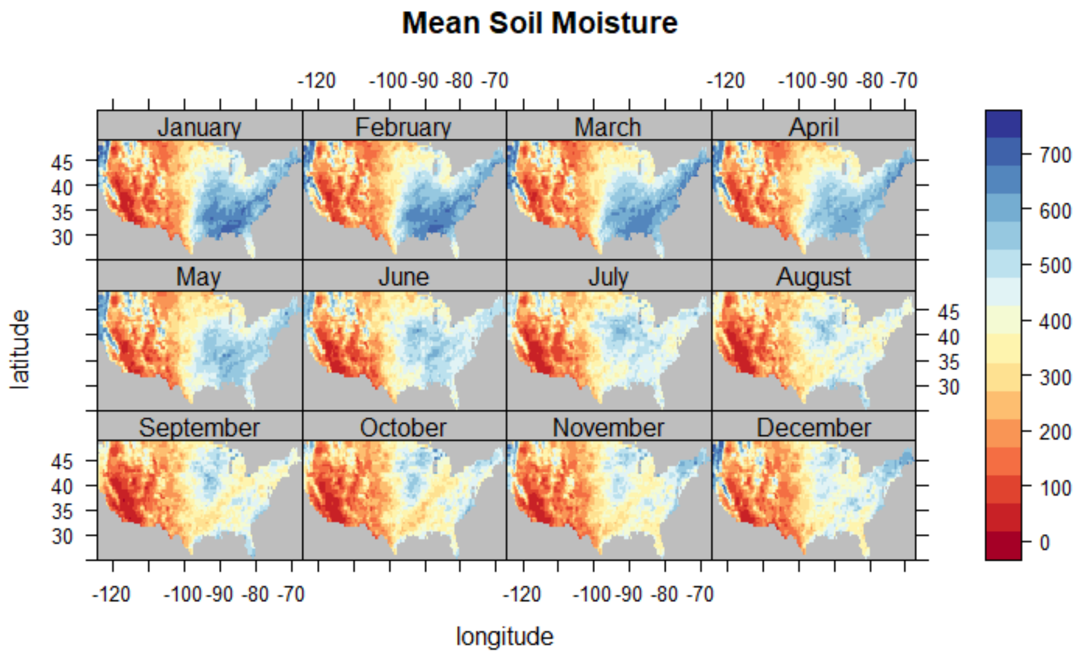



Figure 2: Map of the spatial offset between soil moisture (red) and atmospheric river hits (blue). !



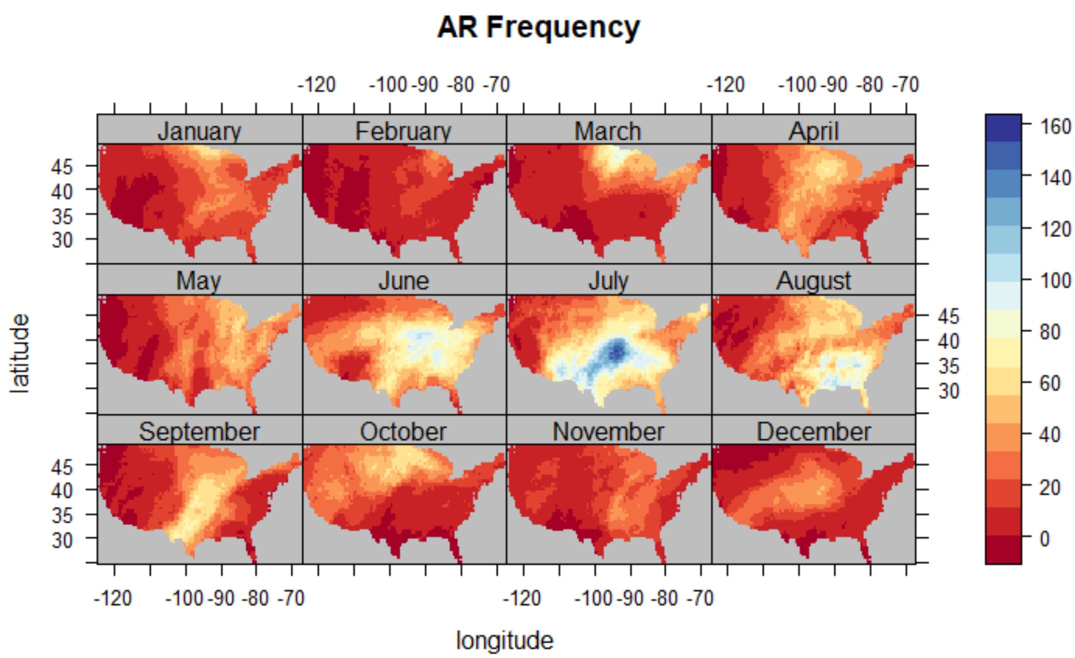




Figure 3: Maps of Mean Soil Moisture (top) and AR Freqency (bottom). Mean soil moisture ranges from 0 (dryest) to 727.4675 mm (wettest) while AR frequency ranges from 0 (no atmospheric river hits) to 153.

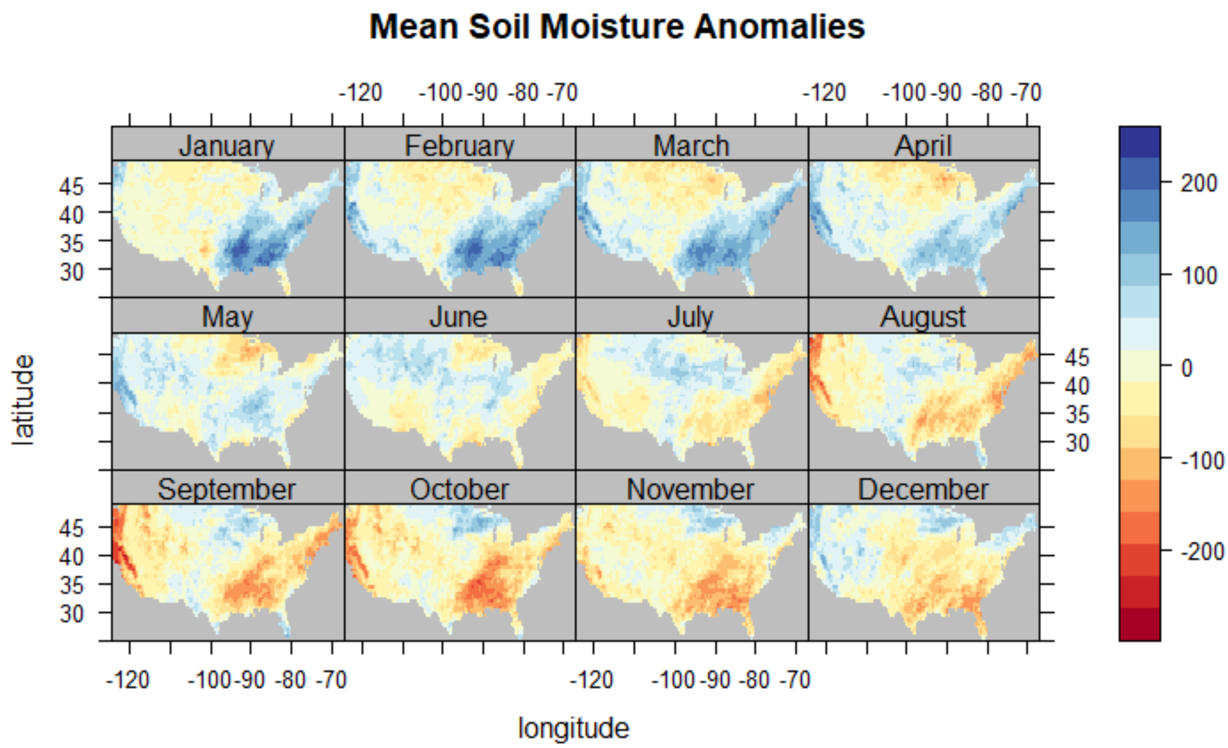



Figure 4: Map of soil moisture anomalies. This is the yearly mean soil moisture (mm) subtracted from monthly mean soil moisture (mm). Positive values represent areas which are wetter than the average while negative values represent areas which are dryer than the average.

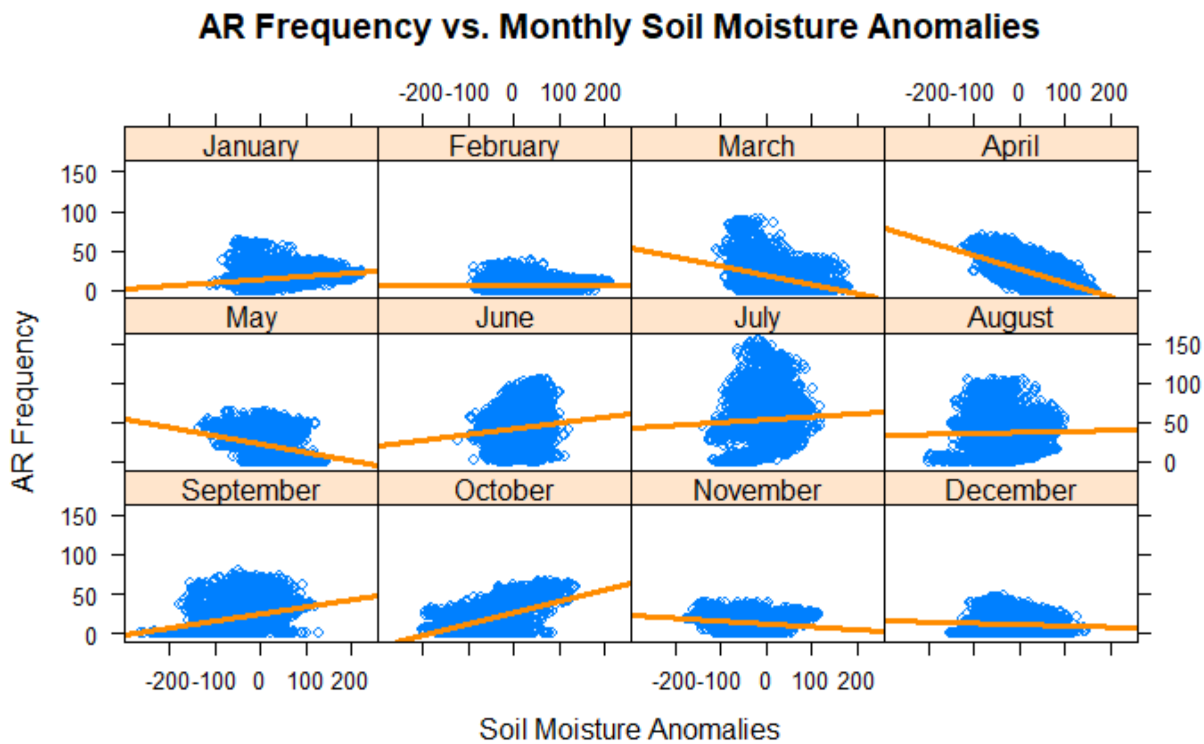



Figure 5: Plots of atmospheric river frequency vs. soil moisture anomalies !

Table 1: Table of 12 months of R-squared values for the plots in Figure 5 along with the correlation.

| **Month** | **R-Squared** | **Correlation** |
|---|---|---|
| January | 0.0404755582 | Positive |
| February | 0.0007155137 | Positive |
| March | 0.1489735721 | Negative |
| April | 0.2937810367 | Negative |
| May | 0.0686709085 | Negative |
| June | 0.0121134295 | Positive |
| July | 0.0024465430 | Positive |
| August | 0.0003781436 | Positive |
| September | 0.0700722455 | Positive |
| October | 0.2707995396 | Positive |
| November | 0.0454418994 | Negative |
| December | 0.0059076043 | Negative |

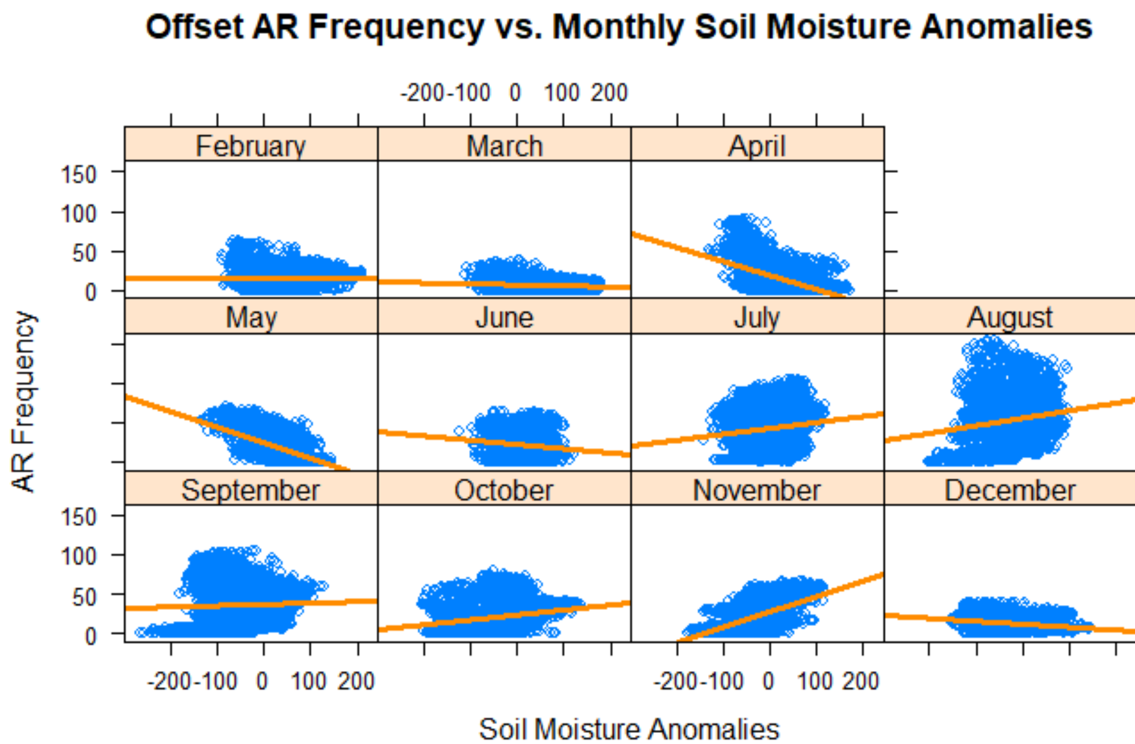



Figure 6: One month offset plots of atmospheric river frequency vs. soil moisture anomalies with AR frequency leading.

Table 2: Table of 11 months of R-squared values for the plots in Figure 5 along with the correlation.

| **Month** | **R-Squared** | **Correlation** |
|---|---|---|
| February | 0.0003296524 | Negative |
| March | 0.0103242040 | Negative |
| April | 0.2509346189 | Negative |
| May | 0.2382372887 | Negative |
| June | 0.0156727033 | Negative |
| July | 0.0167908435 | Positive |
| August | 0.0221170106 | Positive |
| September | 0.0014065786 | Positive |
| October | 0.0393912461 | Positive |
| November | 0.3226564206 | Positive |
| December | 0.0490527351 | Negative |

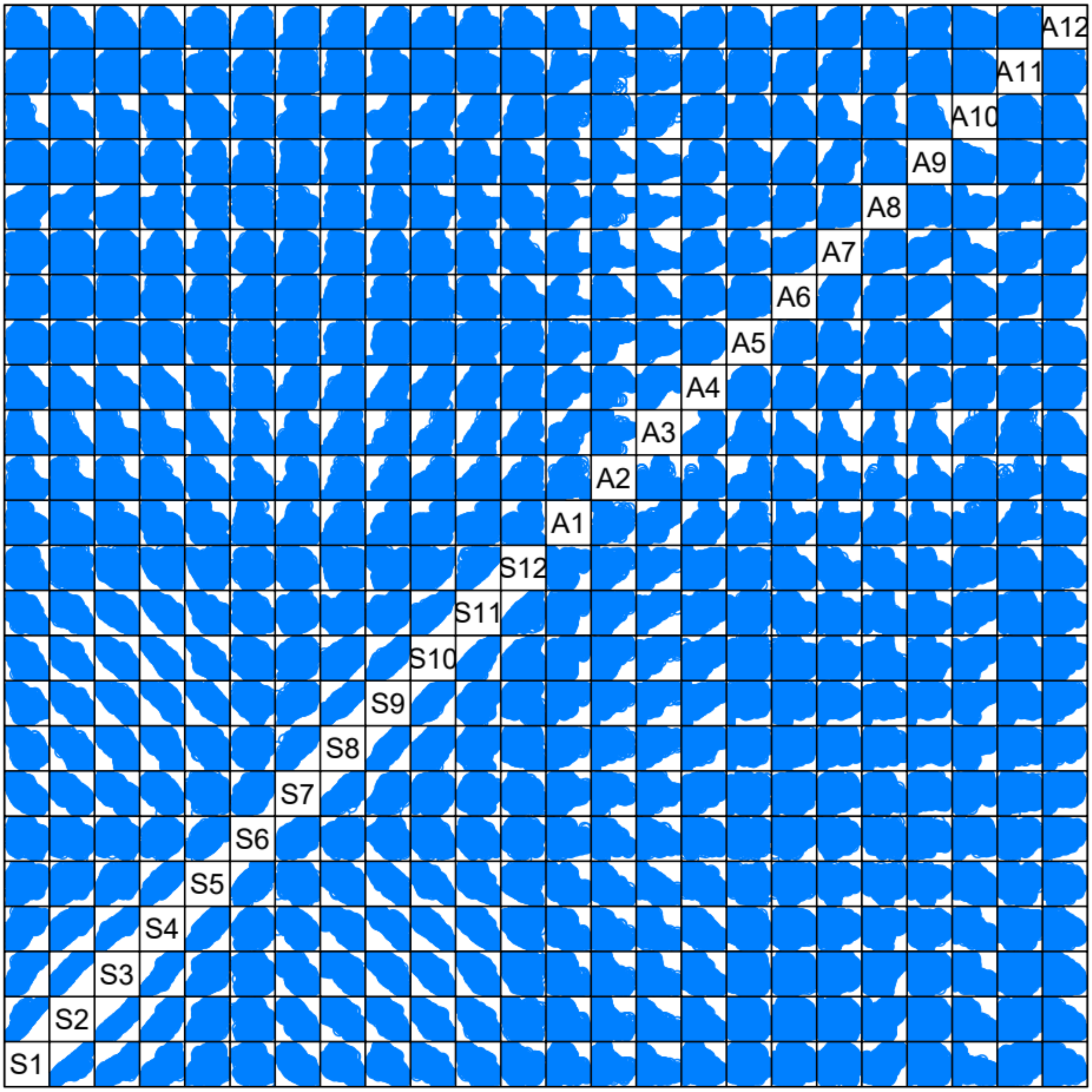



Figure 7: Scatterplot matrix (SPLOM) of each monthly mean soil moisture anomaly (S) and atmospheric river hit month (A) for January through December (1-12). There is a visible relationship between soil moisture anomalies of each month with the following month. There is little evidence of a relationship between soil moisture anomalies and atmospheric rivers.

## 7. References

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